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Graph Recommenders
(in the Browser)

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Introduction / TOC

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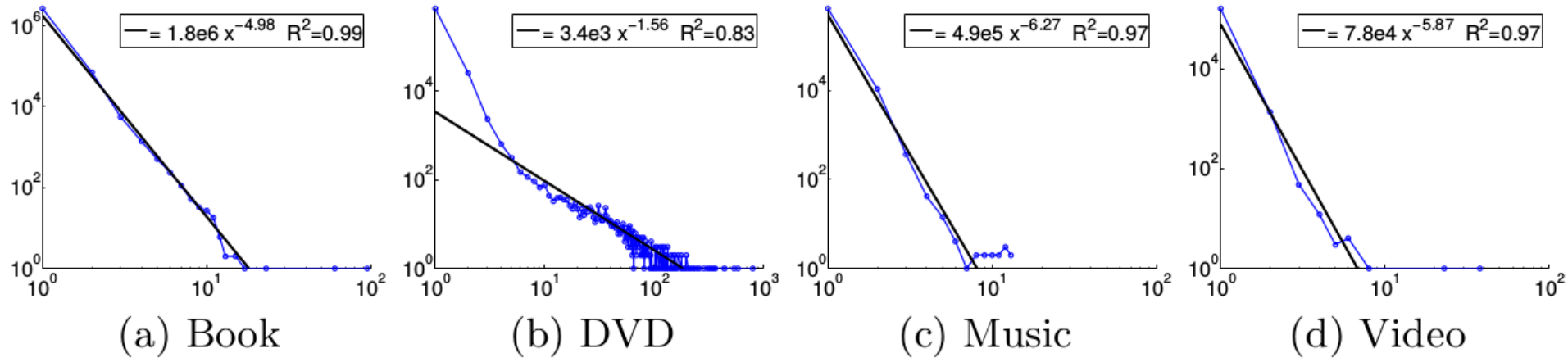
Motivation: The local sphere (idea) 1/2

A study of recommendation cascades (clusters) in an online shopping network of millions of users showed that:

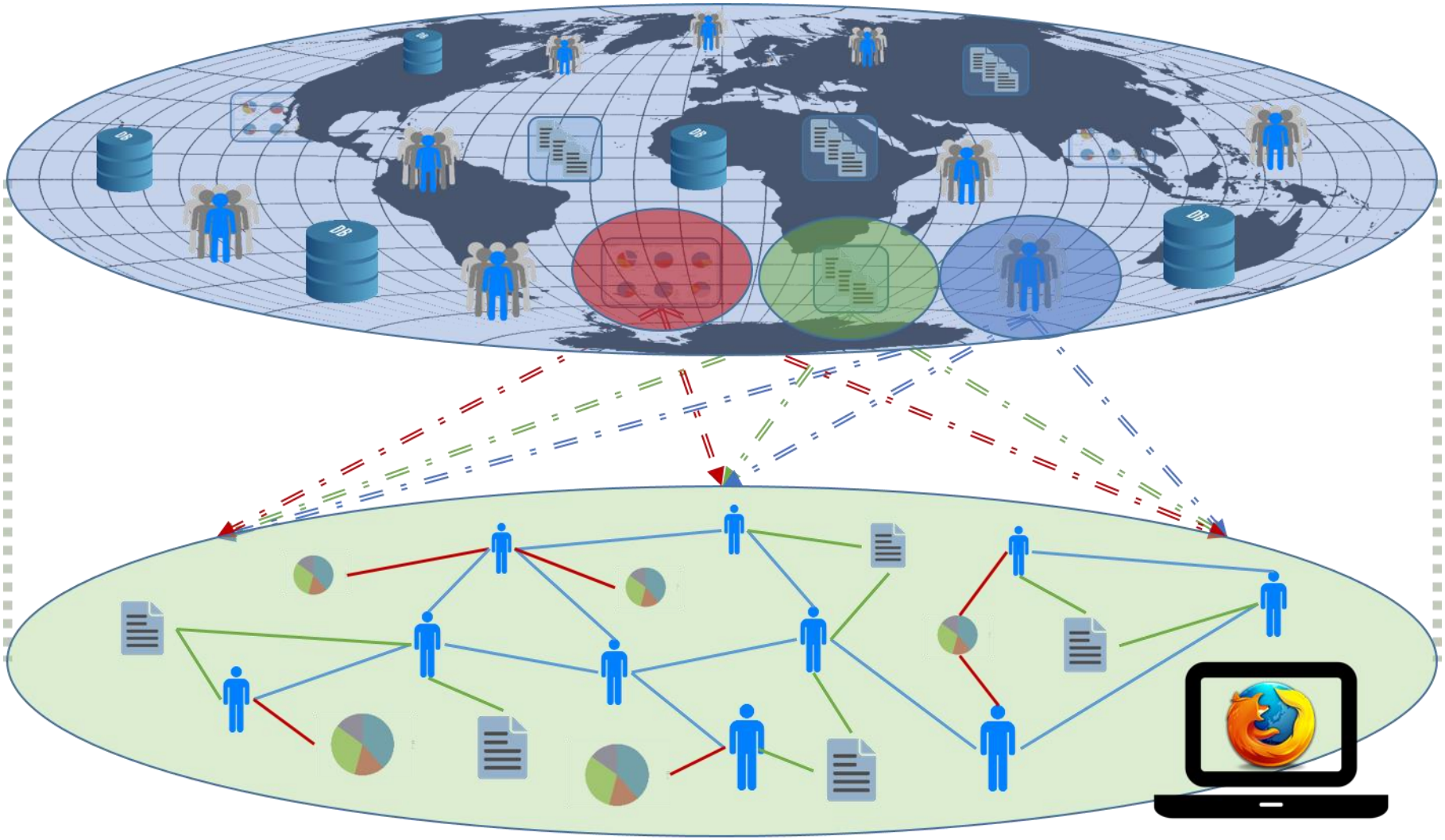
- The average size of cascades was relatively small (maximum ~10 f or all but DVDs)
- The radius of those cascades (graphs) is on the average less than 2 (degrees of separation)



Leskovec, Jure, Ajit Singh, and Jon Kleinberg. "Patterns of influence in a recommendation network." *Pacific-Asia Conference on Knowledge Discovery and Data Mining*. Springer Berlin Heidelberg, 2006.

Motivation: The local sphere (idea) 2/2

Pub/Sub in modern WebApps



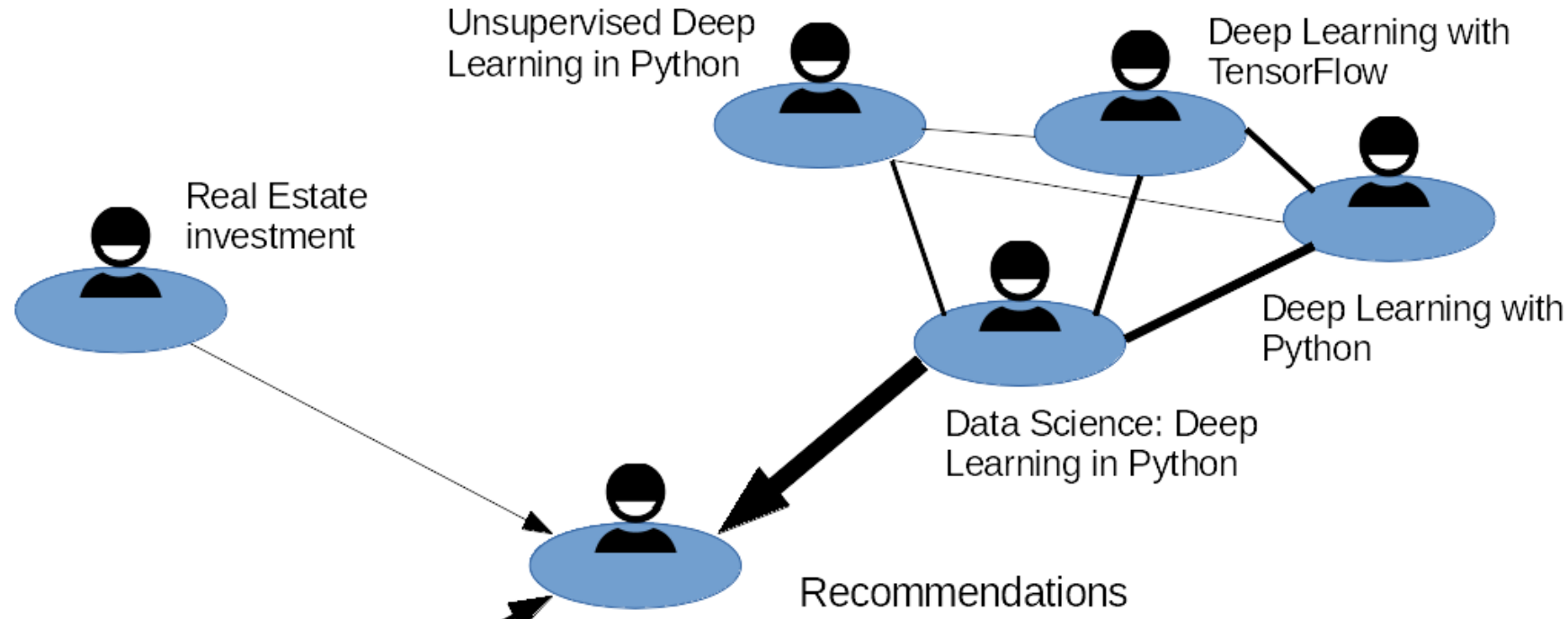
Desired outcome

- Better understanding of the influence factors in graph based recommendations
- Better understanding of the complexity / runtime behavior of graph based recommenders
  - Especially useful for larger graphs outside our experimental scope
- Basis for further experiments in ML on perturbed knowledge bases => “Playground project”
- Working software ;)

Experimental workflow

1. Researcher will navigate to the Website
2. Chooses from several pre-defined graphs
3. Recommendation mode: single / all users
   - We are recommending Udemy courses
4. Recommendations are *approved /rejected* or *rated*
5. The feedback alters the underlying feature vectors
   - This can also affect graph features / metrics (e.g. edge weights through user similarities)
6. Recommendations are re-computed… this cycle continues until researcher has enough data to write a paper about it ;)

Visualization



1. Data Science: Deep Learning in Python
2. Deep Learning with Python
3. Usupervised Deep Learning in Python
4. Deep Learning Prerequisites: Linear Regression in Python
5. Complete Python Bootcamp: Go from zero to hero in Python
6. Investment Portfolio Analysis with Python

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Graph recommender algorithm

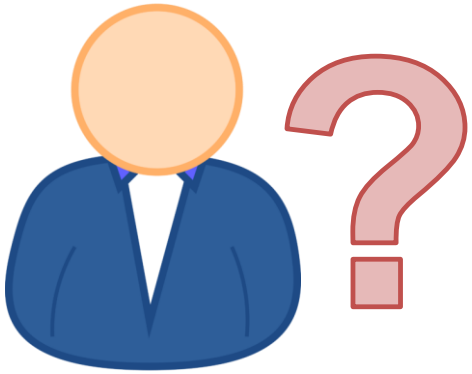
- Not yet determined, but recommenders can build on several factors:
  - Collaborative filtering – recommend what others have done / chosen (the typical amazon recommender)
  - Content based filtering (building a user profile)
    - A model of the user's preference
    - A history of the user's interaction with the recommender
  - Network structure

So which dataset is accessible to us ?

Datasets (anonymized FB graphs)

- Anonymized FB graphs provided by SNAP (Stanford Network Analysis Project)
- 10 FB EGO-graphs: social network from the perspective of one user => shows only relations among friends
- Just the structure is provided
- Content has to be re-generated

  (if necessary)



Enriching anonymized graphs 1/2

```
70 education;concentration;id;anonymized feature 426
71 education;concentration;id;anonymized feature 427
72 education;concentration;id;anonymized feature 428
73 education;concentration;id;anonymized feature 429
74 education;concentration;id;anonymized feature 430
75 education;degree;id;anonymized feature 21
76 education;degree;id;anonymized feature 431
77 education;degree;id;anonymized feature 313
78 education;degree;id;anonymized feature 432
```

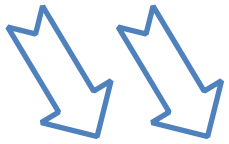
Random fake data generator…?

https://randomuser.me/api/portraits/women/68.jpg

```
{ first_name: 'Monique',
  middle_name: 'Imogene',
  last_name: 'Weimann',
  gender: 'female',
  avatar_url: 'https://randomuser.me/api/portraits/women/68.jpg' }
{ work_end_date: 2015-04-24T08:53:04.456Z,
  work_start_date: 2011-06-11T08:07:46.529Z,
  graduation_date: 2011-03-04T10:59:40.290Z,
  birth_date: 1991-03-09T10:59:40.000Z }
{ employer_id: 'Adams - D\'Amore',
  from_id: null,
  with_id: null,
  location: '00588 South Treside',
  position: 'District Web Administrator',
  projects: [ 'Refined Fresh Chair' ] }
{ hometown: '37317 South Charlotteside',
  location: '26154 South Athena',
  languages: [ 'English', 'Mandarin' ],
  locale: 'en_US' }
```

Enriching anonymized graphs 2/2


```
Course #  Course Title  Level
16.00 Introduction to Aerospace Engineering and Design  Undergraduate
16.00AJ Exploring Sea, Space, & Earth: Fundamentals of Engineering Design
16.01 Unified Engineering I, II, III, & IV (Fall 2005)  Undergraduate
16.02 Unified Engineering I, II, III, & IV (Fall 2005)  Undergraduate
16.03 Unified Engineering I, II, III, & IV (Fall 2005)  Undergraduate
16.04 Unified Engineering I, II, III, & IV (Fall 2005)  Undergraduate
16.050  Thermal Energy  Undergraduate
16.06 Principles of Automatic Control Undergraduate
```



```
Config.UNIVERSITIES holds 7626 distinct entries.
Config.DEGREES holds 195 distinct entries.
Config.SCHOOL_TYPES holds 3 distinct entries.
Config.CONCENTRATIONS holds 152 distinct entries.
Config.CLASSES holds 37 distinct entries.
```

OK – so we have enough data, but how to assign them realistically to our users considering the FB graph?

Modeling a stochastic process

- Our anonymized graph might give us different schools (anonymous features) for 2 connected users

- But which schools should we assign? Random ones?
  - Certainly, the likelihood for 2 people to be acquainted is higher if they attend geographically close schools (MIT / Harvard) than far apart (MIT / TU Graz)
  - What about qualifications / interests / languages etc.??

- We need to base our data generators on stochastic processes resembling reality => Probably a significant project in itself !

Future work

1. Scaling of graph algorithm to real-sized DBs?
2. Implementation of local sphere idea?
   - How to connect to a super-graph
3. Perturbation of graphs:
   - adding / removing nodes / edges
   - Perturbing node feature vectors
   - Targeting specific graph metrics:
     - Centralities
     - Components
     - Flow properties (throughput etc. …)

Thank you!